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Interactive Media Institute
Changes in EEG Behavior through Feedback Presentation

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Abstract. Performance of brain-computer interface (BCI) will depend, to a great extent, on the ability of subjects to control their own electroencephalographic signals (EEG). To this end, it is necessary to follow a suitable training and to provide some type of visual feedback. The objective of this study is to explore the possibility of improving the EEG control via feedback presentation. Eighteen untrained subjects, divided in two groups, were trained using a BCI system based on virtual reality techniques, which submits subjects to a more familiar environment, such as controlling a car to avoid different obstacles. Different types of obstacles were introduced for each group. Significant differences in classification error rates between both groups were obtained during the last second of the feedback period.

Keywords: brain-computer interface, feedback, training techniques, virtual reality

Introduction

Brain-computer interfaces (BCIs) use the electrical activity of the brain recorded during specific mental activities to control an external device. Some BCIs are based on the individual’s capacity to control some feature of electroencephalographic (EEG) activity. To this end, it is necessary to follow a suitable training and to provide some type of visual feedback allowing subjects to see their progress [1,2]. In order to improve the effectiveness of the training process, feedback needs to be attractive, thus motivating subjects to control their EEG signals. To get this objective, virtual reality technology can be used. Effectively, virtual reality is a powerful tool with graphical possibilities to improve BCI-feedback presentation, and has the capability of creating immersive and motivating environments.

The purpose of this study is to continue the work developed in previous research [3]. In this work, a group of subjects was trained using a BCI system, which uses conventional feedback (bar extension), while another group was trained using a BCI system, based on virtual reality techniques, which submits subjects to a more familiar environment, such as controlling a car to avoid puddles. The obtained results showed how subjects were motivated throughout the feedback period to control the car’s movement to avoid the puddle, achieving a good EEG control. However, a worsening of this control was noticed during the last second of feedback, due probably to the fact that subjects did not make an effort when they realized the puddle was almost behind them. To avoid this lost of EEG control, it would be necessary to help subjects to

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maintain concentration during all feedback period. In the study presented in this paper, and with the purpose of improving the EEG control during all feedback period, the same BCI system than the one proposed in [3] has been used, but different obstacles are incorporated at the end of the puddle [4].

1. Materials and Methods

1.1. Subjects and Data acquisition

Eighteen naïve subjects participated in this study (13 male, 5 female, right handed, age 23.3 ±1.4). Two groups of 8 and 10 subjects were formed and referred to as group 1 and group 2 respectively. The EEG was recorded from two bipolar channels with electrodes placed over the right and left hand sensorimotor area. Active electrodes were placed 2.5 cm anterior and posterior to electrode position C3 and C4 according to the 10/20 international system. The reference electrode was placed at FPz position. Signals were amplified by a 4 channel Coulborn V75-08 amplifier and then digitized at 128 Hz by a 12 bit resolution data acquisition card DAQCard-6025E (National Instruments).

1.2. Training protocol and Trial time

The training protocol consisted of 7 sessions, 2 without feedback and 5 with feedback. During each session, subjects were instructed to carry out 160 trials of 8 s each. The training was carried out discriminating between two mental tasks: mental relaxation and imagined right hand movements.

![Figure 1.](image1.png)
The timing of the trial is shown in Figure 1a. Initially, in a scene of continuous movement, the car was driving down the middle of three lanes. At 2 s, a puddle-like obstacle, in the left or right lane, would come into view at the end of the road. If this appeared in the left lane, subjects should imagine right hand movements. If it appeared on the right, they should remain in a relaxed state. At 4.25 s, the puddle was situated beside the car, starting the feedback period when subjects were able to control the movement of the car to the left or right according to the mental task, to avoid the puddle (session with feedback). In sessions without feedback, the car remained in the central lane during the feedback period.

Subjects of group 1 were trained using the feedback based only on the puddle. Subjects of group 2 were trained using the feedback based on the puddle and, in addition, different obstacles located at the end of the puddle [4], specifically, walls (the car must avoid crashing into the wall) and ramps (in this case, the car must reach the ramp that would make the car jump so, the ramp was also located at the end of the puddle but on the opposite lane) as is showed in Figure 1b. With the aim of achieving a more realistic environment, sounds simulating a car engine, puddle splashes, and effects of the obstacles were introduced.

1.3. Signal processing

The signal processing included EEG feature extraction and classification, and was the same than the one used in [3]. The feature extraction consisted of estimating the average band power of each channel in predefined, subject specific reactive frequency bands at intervals of 500 ms (by digitally band-pass filtering the EEG using a Butterworth filter of order 5, squaring the signal and averaging over the 64 samples). The reactive frequency band was manually selected for each subject, checking the largest difference between the power spectra of two 1 second intervals: a reference interval (0.5 s – 1.5 s) and an active interval where a mental task took place (6 s – 7 s). The classification was based on linear discriminant analysis (LDA). Signal processing was done in MATLAB.

For each session, an error time course was computed with a ten times 10-fold cross validation of a linear discriminant (more detail in [3]), for each time point $t = 500$ ms. In sessions without feedback, the extracted feature parameters of the classification time points with the lowest classification error were used to set up the LDA classifier parameters (weight vector) for the following sessions with feedback. In the feedback sessions, the LDA classification result was converted on line to the length $L$ of feedback car’s movement, which was updated on screen every 4 samples (32 ms), to make feedback as continuous as possible. A negative/positive value of $L$ was translated into a left/right car’s displacement, indicating that trial was classified as a left/right trial.

2. Results

To obtain comparative results, an error time course, $Et$ (in percentage), was obtained by calculating the average between the error rates of all sessions with feedback (see Figure 2). Continuous lines and dashed lines represent error curves for subjects of group 1 and group 2 respectively (the results for subjects of group 1 are the ones obtained in [3]). From the eighteen subjects, nine did not show any control in EEG signals (fine lines).
The other nine subjects showed some control in EEG signals and their average error curves during feedback period were below error of 45% (thick lines).

Analyzing the error time courses $Et$ during the last second of feedback period (7-8 s) for subjects who showed some EEG control (thick lines), an interesting difference between the two groups (group 1 and group 2) can be observed. Effectively, curves show how error rates worsen during the last second of feedback when subjects had to avoid only the puddle (group 1), while the presence of an obstacle located at the end of it seems to help subjects to maintain the control of the EEG signals until the end of the feedback period (group 2). As is described in [3], an interesting parameter is the slope of the error time course, which can be used to indicate the steepness of a curve at a particular point. For each time course $Et$, a value $m$ of slope was calculated each 500 ms (see [3] for more detail). A negative/positive value of $m$ means a decrease/increase of the error rate. In this study, only the mean slopes obtained for each subject during the last second of the feedback period (7-8 s) have been analyzed. The mean ± SD slopes over all subjects of each group are represented in Table 1 (MeanG1 and MeanG2 for group 1 and group 2 respectively). Besides, the mean ± SD slopes over all subjects who showed some EEG control (thick lines in Figure 2) have also been calculated of each group (MeanG1Control and MeanG2Control for group 1 and group 2 respectively). Regarding subjects who showed some EEG control, it is interesting to observe how, effectively, the obtained mean slope over subjects of group 1 (MeanG1Control) is positive,

**Table 1.** Mean slopes of the error time courses $Et$ during the last second of the feedback period (7-8 s).

<table>
<thead>
<tr>
<th>Group of subjects</th>
<th>Mean ± SD slopes</th>
</tr>
</thead>
<tbody>
<tr>
<td>MeanG1</td>
<td>1.75 ± 2.49</td>
</tr>
<tr>
<td>MeanG2</td>
<td>-0.67 ± 1.16</td>
</tr>
<tr>
<td>MeanG1Control</td>
<td>3.33 ± 3.15</td>
</tr>
<tr>
<td>MeanG2Control</td>
<td>-1.31 ± 3.01</td>
</tr>
</tbody>
</table>
due to the increase of the $Et$ error rates during this period. However, the obtained mean slope over subjects of group 2 (MeanG2\textsubscript{Control}) is negative, due to the decrease of the error rates. The same remarks applied when all subjects are considered for each group (MeanG1 and MeanG2). Besides, the performed one-way ANOVA revealed significant differences between MeanG1\textsubscript{Control} and MG2\textsubscript{Control} ($F(1,7)=9.18; \text{ } P=0.0191$), and between MeanG1 and Mean G2 ($F(1,16)=4.84; \text{ } P=0.0429$).

3. Discussion

The results obtained suggest how it is possible to improve the EEG control presenting feedbacks whose effects are more immersive and motivating. Significant differences in feedback control between both groups were obtained during the last second of the feedback period. The incorporation of an obstacle at the end of the puddle, at the end of the feedback period, allows the subject to feel immersed and to be taking part in the task of avoiding the puddle during the whole feedback period. The subject manages to maintain concentration until the end of the trial, avoiding a loss of control of the BCI. In BCI systems, training must be as easy and attractive as possible. Changing the feedback presentation makes it possible to modify the behavior of the subject and in turn, their capacity to control the EEG signals. The graphical possibilities of a multimodal interface combining 3D display and sound seems to be a good option to develop training techniques helping subjects to achieve a better control of the BCI.

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References


